BİTLİS EREN ÜNİVERSİTESİ
FEN BİLİMLERİ DERGİSİ

ISSN: 2147-3129 / e-ISSN: 2147-3188

Article Type : Research Article
Received : April 24, 2025
Revised : June 26, 2025
Accepted : September 2, 2025
DOI : 10.17798/bitlisfen.1683303

Year : 2025
Volume : 14
Issue : 3
Pages : 1596-1609

DETERMINANTS OF ELECTROOCULOGRAPHY MEASUREMENTS FOR QUIET EYE DURATION IN ARCHERS VIA PENALTY REGULARIZER

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ABSTRACT

Electrooculography (EOG) is an electrophysiological method used to assess eye movements and the functional status of the retinal pigment epithelium by measuring the potential differences generated during eyeball motion. In recent years, EOG has also been explored as a tool for determining quiet eye (QE) periods in athletes. The QE period refers to the duration an athlete maintains focused visual attention on a target, and it is considered to be closely linked with athletic performance.

The application of EOG in this context is emerging as a novel approach to evaluate and enhance athletes' visual focus and concentration skills. In this study, the relationships between QE period and various free parameters of the athletes were analyzed using penalty approaches (Lasso and Ridge regression). Thanks to this approach, QE periods can be predicted with high accuracy based on the independent variables of individuals without any direct QE measurement for different athletes, and this will contribute to the development of preventive or supportive strategies for performance. The R^2 value for the coefficients of the two regression methods was obtained more than 80% and the mean square deviation was less than 5%.

Keywords: Electrooculography, Quiet eye period, Archer, Regression, Data prediction.

1 INTRODUCTION

Archery is a precision sport demanding technical accuracy, mental resilience, and physiological regulation. Unlike high-intensity team sports, it places a strong emphasis on individual performance. Achieving sustained athletic success thus requires a comprehensive, systematic analysis of biomechanical, physiological, psychological, and technical-tactical factors [1]. Performance optimization in archery relies on a triad of technical proficiency, physical stability, and mental discipline. Given the sport's precision, even minor deviations in technique or posture can significantly impact shot accuracy. Coaches must implement individualized training programs reflecting each athlete's unique characteristics, integrating technological tools like motion capture and wearable sensors for precise monitoring and accelerated feedback [2-4]. This evidence-based, data-informed approach is critical for maximizing performance potential in elite archery.

The QE is a crucial cognitive and visual approach influencing performance, particularly in precision-based sports. Initially described by Vickers (1996), QE refers to the final, steady gaze period just before initiating a motor action [5]. In archery, this "final gaze" typically lasts 300–500 ms on the target prior to and during the release phase [5]. The duration of this fixation is directly associated with attention regulation, processing visual data, and the quality of motor preparation. In precision disciplines, QE duration plays a vital role in optimizing performance, making QE training a key tool for elite athletes [6-7]. Empirical evidence shows elite archers exhibit significantly longer and steadier gaze fixations compared to less experienced counterparts, contributing to increased shot accuracy and consistency [8]. Accordingly, QE should be conceptualized as an integral aspect of cognitive-motor preparation in high-performance contexts, beyond just a visual mechanism. Research confirms that archers mastering QE demonstrate superior technical consistency under pressure and faster recovery from errors [9-10]; elite archers display QE durations 20-30% longer than amateurs [8].

QE duration can be extended through individual training and technological devices. Increasing this duration is crucial for improving focus and shooting accuracy. Coaches can support athletes by incorporating exercises designed to enhance mental focus, training them to recognize and manage distractions to maintain sustained attention on the target [7]. Additionally, deliberate movement strategies, such as encouraging archers to slow down and carefully pause at each step, can provide more time for eye fixation on the target [8]. Beyond these individual methods, technological devices also contribute. Eye-tracking systems allow

coaches to monitor and quantify QE duration by tracking eye movements, while video analysis of shots enables detailed observation of QE duration and eye movements, facilitating the identification of improvement areas [6].

In recent years, the application of Artificial Intelligence (AI) and Machine Learning (ML) in sports has witnessed remarkable growth. These technological advancements offer promising opportunities, particularly in multidimensional domains like athlete health, performance optimization, and rehabilitation. AI and ML facilitate early injury prediction, the development of individualized training programs, and real-time performance analyses [11]. Moreover, the integration of big data analytics and sensor-based technologies in athlete monitoring contributes to clinical decision support systems. Techniques such as deep learning, decision trees, and support vector machines have proven highly effective in assessing injury risk and conducting tactical in-game analyses [12]. These developments are significantly transforming sports from a primarily physical endeavor into a more data-driven and analytical discipline.

An athlete's QE time can be influenced by several parameters. Identifying which of these parameters actively affect QE time can help enhance it. This study, conducted with archers, utilized data optimization techniques, specifically the Lasso and Ridge methods, to determine which parameters significantly impacted the recorded QE times. The optimization process was based on the individual characteristics of the participating athletes. The findings from this research are expected to contribute to the improvement of QE times in archers, thereby potentially enhancing their overall performance.

2 MATERIAL AND METHOD

While detailed EOG data are obtained to measure the QE duration of athletes, it would be useful to develop a system that can predict which parameters will be useful in determining the QE duration. Lasso and Ridge regression methods are some of the known methods in the literature to handle these prediction situations. In the following subsections, we applied both regression approaches to explore the determinants of QE duration.

2.1 Participants

Eighteen archers (nine female and nine male; mean age = 17 years), all of whom had engaged in regular archery training for a minimum of two years, were recruited for participation

in the study. An Ethical Approval Certificate (19956/2020/26/5) for conducting the study was obtained from the Osmaniye Korkut Ata University Scientific Research and Publication Ethics Committee. All participants, along with their parents and coach, signed an informed consent form prepared in accordance with the Declaration of Helsinki. Beyond the aforementioned criteria, participant eligibility further mandated the absence of any chronic health issues and complete participation in all designated parameter measurements. Exclusion criteria were applied to ensure data quality and participant suitability. Participants were excluded if their EOG recordings exhibited excessive noise or were otherwise unsuitable for analysis. Additionally, individuals with less than two years of archery experience, those diagnosed with neurological or ophthalmological disorders that could influence eye movements, or individuals who sustained an injury within the last six months impacting archery performance were not included.

The mean height of the archers was 160.93 ± 11.33 cm, and their mean body mass was 63.67 ± 19.34 kg. Each athlete's total performance score was recorded following three sets of six shots, for a total of 18 arrows per participant. Athletes completed three sets, each consisting of six shots. Missed shots were scored as zero, and no second attempts were permitted. The shots were fired from distances of 30 to 50 meters.

The variables to be used in the next stages of the analysis and their importance in our research are presented in the Table 1.

Table 1. The role and rationale for variable selection

Variable	Reason
Age	It is directly related to the level of neurodevelopmental maturity and attention span.
Gender	There may be gender-related differences in biological and psychological attention strategies.
Height / Weight	It affects trunk stability and balance and can affect the steady aiming process.
Training Duration	Long training duration enables the development of higher-level cognitive skills such as QE.
R/L_Leg Length	It can directly affect focus by affecting body symmetry during a fixed standing position.
Archery Scores (Hor/R/L)	It is necessary to control the effect of QE duration on individual performance.
CRDL / CRDR	Provides information about the functional quality of the visual system. May affect QE duration associated with eye movements.
BodyAwarenessScore	It has been shown in the literature that individuals with higher levels of psychophysiological awareness can have longer QE duration.

*R/L_Leg Length: Right, Left Leg lenght.

** Composite Reach Distance_Right: CRDR, Composite Reach Distance_Left: CRDL.

Table 2 provides descriptive characteristics of archers.

Table 2. Descriptive statistics of archers age, height and weight

Parameters	mean	std	min	25%	50%	75%	max
Age	17,33	1,44	10	11	14	15,75	19
Training Duration (year)	3,17	2,74	0	1,62	2	4,5	12
Body Heigth (cm)	160,93	11,33	142	153,25	158,25	171	180
Body Weigth (kg)	63,67	19,34	37	51	57,75	71,75	115
R_Leg_Length (cm)	85,67	6,77	75	82	84	90	99
L_Leg Length (cm)	85,5	6,45	75	82	84	90,75	96

The 25th, 50th, and 75th percentiles (25%, 50%, 75%) correspond to the first quartile, median, and third quartile, respectively, offering insights into the data distribution.

2.2 The Data Collection with EOG in Assessing QE Durations of Athletes

EOG's ability to record eye movement-related potential shifts has made it an alternative or complementary method for quantifying QE periods. The portability and lower cost of EOG equipment enhance its applicability in real-world sports settings.

An electrooculography (EOG) device was employed to determine the quiet eye (QE) duration of the participants. Eye movements were recorded using the Biopac MP100 system (BIOPAC Systems, Inc., Santa Barbara, CA, USA) during the athletes' shooting sessions. The corneal-retinal potential was amplified via the EOG100C Electrooculogram amplifier, integrated with the recording system. Data were collected at a sampling rate of 200 Hz and analyzed using BIOPAC AcqKnowledge Analysis Software (ACK100W). Horizontal and vertical eye movements were recorded separately for both the right and left eyes. All measurements were conducted during arrow shooting.

QE duration was defined as the time interval from the initiation of visual fixation until the release of the arrow. The onset of the QE period was determined retrospectively from the moment of the shot. In the EOG recordings, the QE period was identified as the amplitude range within 3 degrees (peak-to-peak) prior to arrow release. The QE offset was marked by the observer, coinciding with the auditory cue of the arrow leaving the bow. Recordings with excessive noise were excluded from analysis. All participants demonstrated fixation durations exceeding 100 ms, remaining within the 3-degree range.

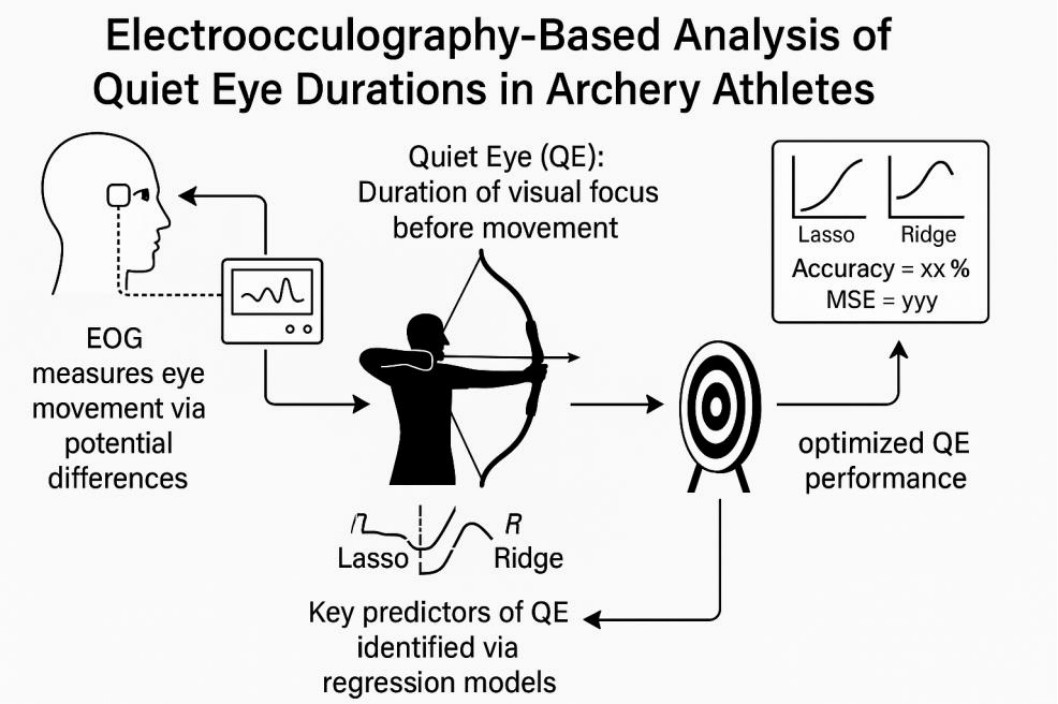


Figure 1. Schematic representation of prediction process [13].

Synthetic data generation was implemented to broaden the model's generalizability. This process was executed under controlled conditions primarily to alleviate the impact of small sample sizes, thereby fostering enhanced model generalization and preventing overfitting. The robust accuracy figures obtained from the model's outputs underscore the success of this methodology.

2.3 Data Analysis with Ridge and Lasso Regression Methods

Regression analysis is an essential statistical approach employed to explore and quantify the relationship between a response variable and one or more predictor variables. However, in high-dimensional datasets particularly when the number of predictors exceeds the number of observations traditional linear regression models are prone to overfitting. To address this issue, **regularization techniques** such as **Lasso (Least Absolute Shrinkage and Selection Operator)** and **Ridge Regression** are employed. These methods enhance generalization by constraining the model's complexity, effectively preventing overfitting and improving predictive performance [14].

Ridge regression is a regularization technique designed to reduce model variance by shrinking the coefficients. It incorporates an L2 penalty, which is the sum of the squared coefficients, into the loss function. This penalty discourages large coefficients, pushing them closer to zero but not exactly zero. The objective function of Ridge regression is:

$$\min_{\beta}\left\{\sum_{i=1}^{n}(y_i - x_i^T\beta)^2 + \lambda\sum_{j=1}^{p}\beta_j^2\right\} \quad (1)$$

where y_i is the target value, x_i is the feature vector for the $\boldsymbol{i}$-th observation, β are the model coefficients, $\lambda \geq 0$ is the regularization parameter that controls the strength of the penalty [15].

Lasso regression is a regularization technique that applies an L1 penalty, which is the sum of the absolute values of the model coefficients. This penalty can shrink some coefficients exactly to zero, effectively removing less relevant features from the model. As a result, Lasso not only helps prevent overfitting but also serves as a powerful feature selection method. The objective function of Lasso regression is defined as:

$$\min_{\beta}\left\{\frac{1}{2n}\sum_{i=1}^{n}(y_i - X_i\beta)^2 + \lambda\sum_{j=1}^{p}|\beta_j|\right\} \quad (2)$$

where y_i is the observed response, X_i is the vector of predictor for the $\boldsymbol{i}$-th observation, β is the vector coefficients, $\lambda \geq 0$ is the regularization parameter controlling the strength of the penalty.

Lasso has advantages over Ridge, especially in cases where unnecessary variables need to be eliminated (sparse data sets) [16]. Lasso simplifies the model and increases interpretability by making some coefficients zero. Ridge reduces the coefficients when including all variables in the model, so it is more stable in cases of multicollinearity.

The data in Table 3 will be used for data analysis. At this stage, we prepare the data used in the next phase. QE_Hor, QE_R and QE_L are determined individually for two models with the rest 14 independent variables.

Table 3. Descriptive statistics of performance parameters.

Parameters	Mean	SD	Min	25%	50%	75%	Max
Archery Score (Hor)	40,33	13,58	7	37,5	40,5	50,75	57
Archer Score (R)	38,5	15,29	5	34	40,5	51	55
Archery Score (L)	40,72	16,12	6	36,5	44	53,5	58
QE_Hor (in seconds)	0,81	0,46	0,22	0,53	0,7	0,91	1,94
QE_R (in seconds)	0,59	0,39	0,2	0,34	0,53	0,65	1,67
QE_L(in seconds)	0,71	0,31	0,26	0,49	0,64	0,93	1,49
CRDR (in cm)	81,08	10,48	62,34	73,06	83,92	89,31	95,06
CRDL (in cm)	80,32	11,32	54,98	76,49	83,33	87,13	96,67
Body Awareness Score (in points)	91	15,73	54	81	93,5	101,75	115

**Archery (Hor)/(R)/(L) scores (in units of points) are the arrow shooting scores obtained by archers while taking horizontal/right/left measurements with EOG.*

The target variables are QE_Hor, QE_R and QE_L. All variables have a numerical value. Both of Ridge and Lasso methods use same amounts of data. The ratio of test and training data has a value of 20:80. The steps of the analysis algorithm can be viewed in Figure 2.

In the analysis, synthetic data generation was performed to increase the generalization performance of the model and to expand the size of the dataset. Synthetic data was obtained by adding small-scale normally distributed noise to randomly selected examples from the original dataset. During this process, low-variance random deviations were applied independently to each input feature; similarly, a small random noise was added to the target variable (output). Thanks to this method, new examples were created that reflect the natural variations of the original examples in both the input and output spaces. The synthetic examples generated were combined with the original data and used in model training. This approach offers an effective strategy in terms of reducing overfitting and making the model more stable, especially in datasets with small sample sizes.

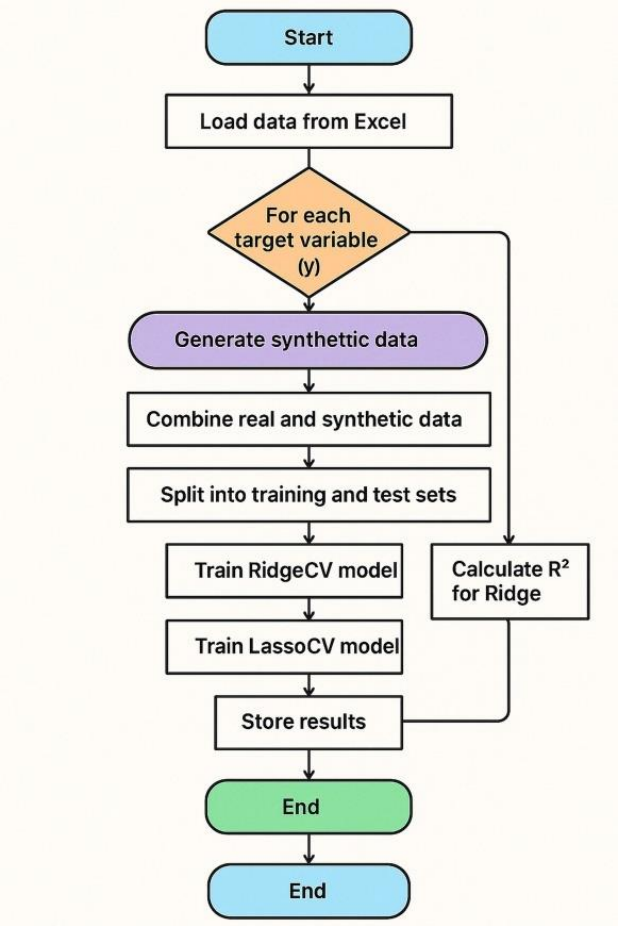


Figure 2. The flow chart of the analysis.

The results given by the models are shown in Table 4.

Table 4. Prediction results of Ridge and Lasso methods.

Parameters	R^2_Ridge	α_{Best}_Ridge	MSE_Ridge	R^2_Lasso	α_{Best}_Lasso	MSE_Lasso	Better Model
QE_Hor (in seconds)	0,847326	1,592283	0,034188	0,801001	0,004977	0,044561	Ridge
QE_R (in seconds)	0,908941	0,067342	0,016608	0,909058	0,000100	0,016586	Lasso
QE_L (in seconds)	0,933835	0,298365	0,003954	0,935428	0,000534	0,003859	Lasso

R^2 indicates the explanatory power of the independent variables on the target variables. As it approaches one, the success of the model increases.

The mean square error (MSE) was utilized as the principal benchmark to gauge the efficacy of both models. Consequently, models with lower MSE values are regarded as more proficient in forecasting.

Ridge regression includes all variables in the model; it reduces the coefficients but does not reset them. Lasso, on the other hand, removes some variables from the model by completely resetting them to zero, and performs variable selection. While some variables (e.g. Gender, Weight) are reset in the Lasso model for QE_Hor, the Ridge model keeps them all. For QE_L, the BodyAwarenessScore parameter has a strong effect in both models. While variables such as RLeg are kept in the Lasso model for QE_R, variables such as Gender and Height are reset.

3 RESULTS AND DISCUSSION

A limitation of this study is the restricted sample size of 18 athletes, which may impede statistical generalization. Consequently, the findings should not be directly extrapolated to populations of athletes varying in age, experience level, or sport. Cohen's f^2 statistic was employed to assess the adequacy of the sample size by quantifying the effect size of the independent variables on the dependent variable in the regression models. A larger f^2 value indicates a stronger explanatory power of the independent variables on the dependent variable. Cohen's strength of association parameter is given as

$$f^2 = \frac{R^2}{1 - R^2} \tag{3}$$

Table 5. Prediction results of Ridge and Lasso methods.

Cohen_f^2	f^2_Ridge	f^2_Lasso	Power_Lasso/Reidge
QE_Hor (in seconds)	3,349	3,02	1,0
QE_R (in seconds)	12,466	16,031	1,0
QE_L (in seconds)	13,268	11,572	1,0

The fact that $f^2 > 4$ reveals that our model establishes a very strong relationship with the variables. Also when the power analysis was performed, the result being unity as indicated in Table 5 shows that the data is more than sufficient to detect this relationship statistically.

In this study, the effects of Ridge and Lasso regression methods on regression coefficients for three different target variables (QE_Hor, QE_R and QE_L.) were analyzed. Ridge regression keeps all features in the model with the penalty function based on the L2 norm and only reduces their effects. This situation results in the effects of the features approaching zero but not completely disappearing. This method has the potential to produce stable and balanced results especially in highly correlated data. On the other hand, Lasso regression performs a natural feature selection by reducing the coefficients of some features to zero with the penalty function based on the L1 norm. In this way, simpler and interpretable models are created; some variables are completely prevented from being included in the model. The best values of alpha depending on the descriptive and performance values of the archers are given for two models as in the Figure 3.

Ridge regression includes all variables in the model; it reduces the coefficients but does not reset them (Figure 3 left column). Lasso, on the other hand, removes some variables from the model by completely resetting them to zero, and performs variable selection (Figure 3 right column). For QE_Hor, some variables (e.g. Gender, Weight) are reset in the Lasso model, while the Ridge model keeps them all. For QE_L, the BodyAwarenessScore parameter has a strong effect in both models. For QE_R, variables such as RLeg are kept in the Lasso model, while variables such as Gender and Height are reset.

A limitation of the present study is its relatively modest sample size of 18 athletes, which inherently restricts the statistical generalizability of the findings. Consequently, direct extrapolation of these results to athlete populations differing in age, experience level, or sporting discipline should be exercised with caution. While the EOG method utilized for measuring QE duration offers advantages in terms of portability and cost-effectiveness, it may not possess the same level of precision and sensitivity in capturing nuanced eye movement data as more advanced, laboratory-based eye-tracking systems. Furthermore, the scope of this investigation was confined exclusively to the sport of archery. It is plausible that QE duration and the factors influencing it may exhibit substantial variability across sports demanding distinct motor skills. Finally, athlete performance assessment was based solely on discrete single-shot attempts, precluding the examination of longitudinal changes or adaptive processes over extended training periods.

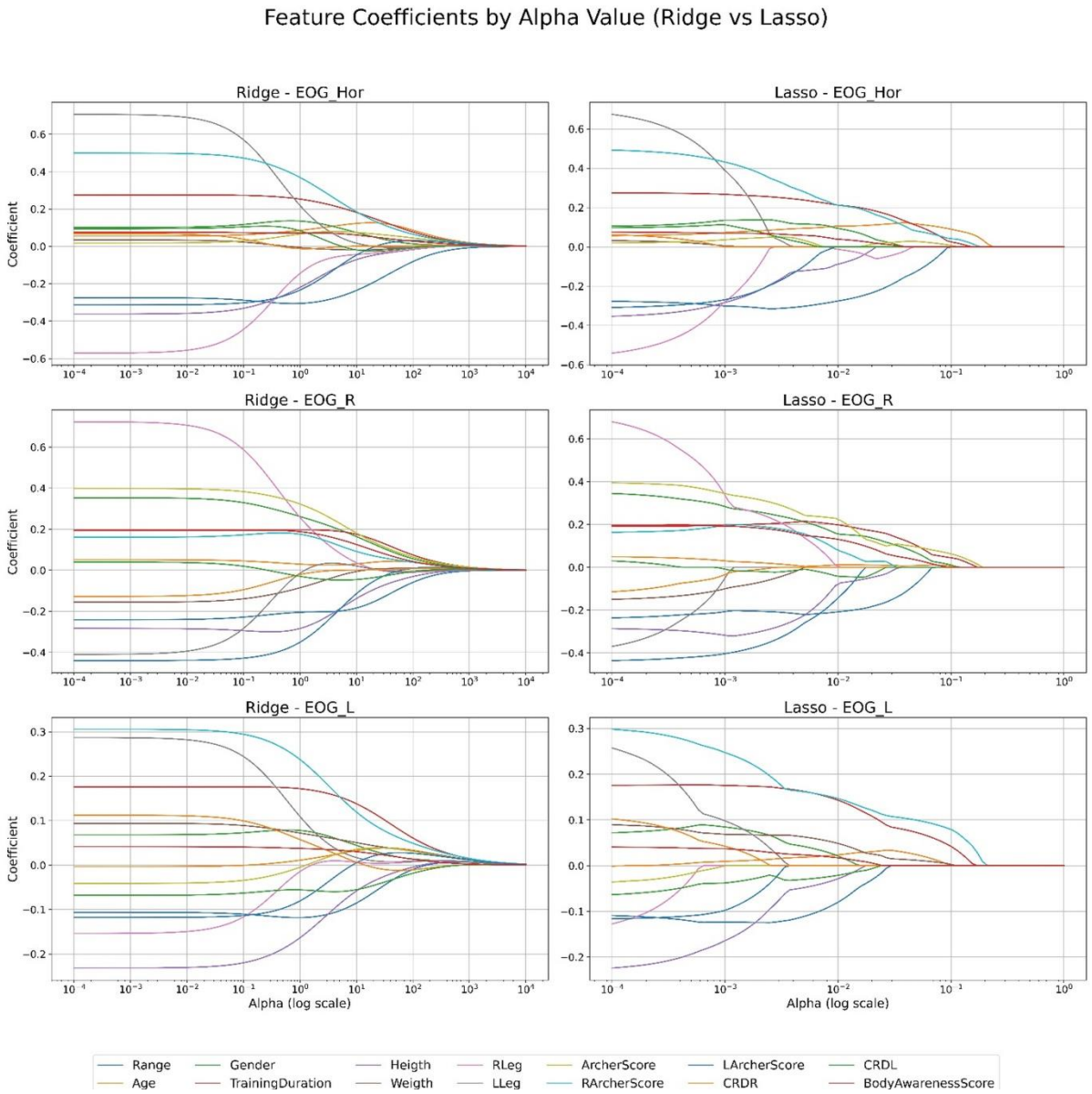


Figure 3. The alpha values are presented in relation to the corresponding feature coefficients. The left panel illustrates the results obtained using the Ridge regression model, while the right panel shows those derived from the Lasso regression model.

4 CONCLUSIONS

The application of Lasso and Ridge regression methods within sports science research is well-established in the literature, with notable applications in various athletic domains, including hockey and basketball [17, 18]. These advanced statistical techniques have been systematically employed to evaluate and analyze athlete performance. Specifically, they have facilitated the identification of distinct analytical objectives through the examination of diverse athlete-specific features. For example, in a study focusing on hockey players, Lasso and Ridge regression were utilized to model key mechanical variables, such as maximum horizontal force

(F_0), maximum speed (V_{max}), maximum horizontal power (P_{max}), and performance across sprint/change-of-direction (COD) intervals [17]. Analogously, both regression methods have been instrumental in assessing the offensive and defensive contributions of basketball players, leveraging detailed NBA match commentary data [18].

In the present study, both Lasso and Ridge regression techniques were similarly employed to determine the QE duration, a critical factor influencing archers' performance. Collectively, these aforementioned studies and our current research highlight the substantial relevance and utility of Lasso and Ridge regression in sports science. These statistical tools not only enable the exploration of the biomechanical underpinnings of athletic performance but also facilitate the objective evaluation of individual player contributions, even within team-based sports contexts.

When the model outputs are evaluated based on the target variable; it is observed that variables such as CRDL and LArcherScore are effective in Ridge regression for QE_Hor, while CRDL maintains its importance in Lasso regression, but some variables are excluded from the model by being reduced to zero. While RLeg, ArcherScore and LArcherScore stand out in Ridge model for QE_R; while RLeg maintains its importance in Lasso model, it is observed that variables such as Gender and Height are reduced to zero in some regulation coefficients. For QE_L, BodyAwarenessScore variable is consistently high in both models; this shows that this feature plays a decisive role in the estimation process.

As a result of the comparative evaluation, it is concluded that Ridge regression is suitable for optimizing the overall model performance by preserving the contributions of all variables, while Lasso regression offers simpler and more interpretable models by making variable selection. While the Lasso method can be preferred especially in applications working with a limited number of variables, the Ridge method offers an effective alternative in order to reduce multicollinearity and balance the overall variance. In addition, the ElasticNet approach, which combines the advantages of both methods, is suggested as a potential method that should be evaluated in future studies.

Conflict of Interest Statement

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The study is complied with research and publication ethics.

Artificial Intelligence (AI) Contribution Statement

This manuscript was entirely written, edited, analyzed, and prepared without the assistance of any artificial intelligence (AI) tools. Figure 1 was generated by ChatGPT.

Contributions of the Authors

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by all authors, and they read and approved the final manuscript.

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